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The Adoption of Integrated Pest Management Technologies by Vegetable Growers

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Abstract

Factors influencing the adoption of Integrated Pest Management (IPM) techniques are studied using survey data from individual vegetable producers from Florida, Michigan, and Texas. Farmers who adopt IPM tend to be less risk averse and use more managerial time on farm activities than nonadopters. Adopters are also more likely to operate large, irrigated farms and use more family labor. Locational factors and the type of crop grown are also influential in IPM adoption. The analysis is based on a logit framework and introduces adopter categories first conceptualized by rural sociologists.

Keywords: Integrated Pest Management, technology adoption, diffusion of innovations, vegetables

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Introduction

Synthetic pesticides were first actively marketed in the United States in the late 1940's, and their use has since played an integral role in the technological advances that have reduced agricultural labor requirements by half and doubled total factor productivity (USDA, 1992). Pesticide use, however, has also caused health and environmental concerns (Cooper and Loomis, Hallberg, Harper and Zilberman, and Mott). Food safety considerations about pesticide residues are especially important in fruits and vegetables, since these commodities are often consumed with little postharvest processing (National Academy of Sciences). In addition, fruit and vegetable production is particularly intensive in pesticidal inputs. In 1990, pesticide expenditures per acre by fruit and vegetable growers were nearly seven times the agricultural average; U.S. farmers as a whole spent approximately $16 per acre for pesticides, while fruit and vegetable growers spent more than $100 per acre (USDA, Gianessi and Puffer).

Integrated Pest Management (IPM) techniques were designed to meet some of these health and environmental concerns and to address the problem of pest resistance to pesticides.[1] IPM combines biological, cultural, and chemical pest control techniques to reduce pest infestation to economically acceptable levels (Gianessi and Puffer). While IPM gained prominence in the late 1960's and first received significant Federal support in 1972, IPM adoption has moved quite slowly (Virginia Cooperative Extension Service).

There is a rich literature on the adoption of technological innovations in agriculture (Feder, Just, and Zilberman). Early research focused on the diffusion process: after a slow start in which only a few farmers adopt the innovation, adoption expands at an increasing time rate. Later, the rate of adoption decreases as the number of adopters begins to exceed the number of farmers who have not yet adopted. Finally, adoption asymptotically approaches its maximum level, until the process ends.

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[1]The Office of Technology Assessment (OTA) defines IPM as "the optimization of pest control in an economically and ecologically sound manner, accomplished by the coordinated use of multiple tactics to assure stable crop production and to maintain pest damage below the economic injury level while minimizing hazards to humans, plants, and the environment." According to the Council on Environmental Quality, IPM relies on "a systems approach to reduce pest damage to tolerable levels through a variety of techniques including predators and parasites, genetically resistant hosts, natural environmental modifications, and, when necessary and appropriate, chemical pesticides." IPM is likely to play a lead role in the transition from a chemical-intensive to a low-input sustainable agriculture.

This process results in an S-shaped[2] diffusion curve, first discussed by rural sociologists and introduced to economics by Griliches in 1957.[3]

Economists and sociologists also want to understand what causes adoption rates to differ and what constrains the rapid adoption of innovations. Several researchers have examined the influence of farmers' attributes on the adoption of agricultural innovations (Rahm and Huffman, Caswell and Zilberman). In the past, most adoption studies focused on technological innovations that increase productivity. Recent interest has shifted toward studies on the adoption of environmentally preferable technologies. The adoption of IPM techniques has recently been analyzed by Kovach and Tette for New York apple producers, J. K. Harper and others for Texas rice farmers, and McNamara and others for Georgia peanut growers.

The objective of this paper is to use survey data from individual vegetable producers in Florida, Michigan, and Texas to identify and quantify factors or attributes that influence IPM adoption decisions. The identification and quantification of these factors will allow an increased understanding of the process of IPM adoption and will help provide policy guidance to promote adoption. Most previous empirical studies have been limited to a local setting (county or clusters of counties) and have used mail or phone surveys. These surveys often have low response rates and are, consequently, subject to response bias.[4] In comparison, the information used in this study was obtained through personal interviews conducted by trained and experienced enumerators. This study is also unique in that we consider three States, each with a different degree of IPM adoption.

Florida, Michigan, and Texas are among the most important vegetable-producing States in the Nation. These States were selected in the survey because they cover a wide range of climates and produce a wide variety of vegetables, including high-consumption items such as fresh tomatoes, onions, snap beans, sweet corn, cucumbers, and watermelons. Of the three States, Florida had the largest acreage in its vegetable farms, with 358,600 acres planted in 1990, followed by Texas, with 205,600 acres, and Michigan, with 159,200 acres (USDA, 1991). Pesticides were a very important input in vegetable production in all three States. In total, more than 80 percent of these acres were treated with insecticides in 1990, more than 75 percent were treated with herbicides, and more than 50 percent were treated with fungicides.

Sociological Views on the Adoption of Innovations

Rural sociologists conceptualize the innovation decision as a process comprised of several stages (Rogers). The farmer sequentially becomes aware, seeks information, and forms an opinion about the innovation. Next, the farmer decides whether or not to adopt. If the decision favors adoption, implementation follows. The process ends with confirmation of the decision or its eventual reversal. A major difference between this process and other types of decisionmaking is the asymmetric

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[2]S-shaped diffusion was first observed by the French sociologist Tarde in 1903. As Rogers notes, Tarde observed that the S-curve took off when opinion leaders used the new idea. Tarde also offered his "laws of imitation," in which adoption is more likely for innovations that have some similarity to ideas already accepted. This principle has been widely used in sociological studies of innovations. A similar notion is used in educational psychology in which "advance organizers" facilitate the acquisition of new information by anchoring it to existing knowledge (Slavin, p. 85).

[3]As Griliches observes, the choice of functional form for the diffusion curve is somewhat arbitrary. The cumulative normal and the logistic functions are often used to represent the S-shaped diffusion process. Since these two functions produce essentially the same results, most researchers use the logistic for its relative simplicity. The logistic can be expressed as: $P = K / [1 + e^{-(a+bt)}]$, where K is the long-run upper limit on adoption, P is the percent of adopters at time t, and a and b are logistic parameters. Parameter b is interpreted as the mean "rate of acceptance of the new technology" and parameter a is a constant of integration related to the extent of adoption at time $t = 0$. The parameters of the logistic function can be statistically estimated using time-series data.

[4]The average response rate from six recent adoption studies in agriculture was approximately 60 percent, with a range of 17 to 89 percent.

uncertainty involved in deciding between the new and the known techniques. The average time required for this process varies across innovations and depends on the characteristics of the innovation, as perceived by the farmers.

Characteristics of Innovations and Their Rate of Adoption

According to Rogers, five characteristics of an innovation are essential to explain its rate of adoption: (1) the perception that the innovation is better than the traditional practice, due to economic or social factors, (2) its compatibility with tradition and past experience, (3) its complexity, (4) the feasibility that the innovation can be tried/experimented on a limited basis, and (5) the visibility of the results of the innovation.

The process of IPM adoption in the United States is now more than 20 years old, but far from complete. The slow rate of diffusion of IPM appears to be related to its characteristics, as listed above. First, given the stochastic nature of yields and production costs, quantifying the economic advantage of IPM is difficult for growers, at least in the short run. Second, unlike traditional chemical methods, which provide the farmer with precise recommendations, IPM is less precise and its recommendations are often in conflict with a farmer's intuition. For example, a recommendation to do nothing is inconsistent with the farmer's traditional notion of pest control. Also, IPM is often at odds with a grower's quality needs; for example, to control cosmetic damage (Kovach and Tette). Third, IPM is a complex, knowledge- and information-intensive technology (Hall and Duncan). Bultena reports that 49 percent of Iowa farmers acquainted with IPM thought that it was "complicated and difficult to use." Fourth, due to production externalities, experimenting with IPM on small portions of the farm may be difficult. Finally, results of using IPM are not clearly evident. It has been observed that farmers are naturally "skeptical when presented with an ill-defined departure from a recognized practice" (Office of Technology Assessment).[5]

Adopter Categories

Rural sociologists recognized early that essential differences among farmers can explain why they do not adopt an innovation at the same time. Rogers uses a time continuum to classify adopters into five categories based on their innovativeness, defined as the degree by which a farmer is relatively earlier in adopting, compared with other members in the system. Because many human attributes (physical or psychological) are normally distributed, Rogers hypothesized that the time to learn a given task is also normally distributed. Furthermore, he argued that substituting a social system for an individual, also leads to the normal distribution, which in the cumulative form approximates the typical S-shaped diffusion curve. For that reason, Rogers used the standard normal distribution to define adopter categories.

Farmers in the first category are the "innovators." These individuals are characterized as venturesome and willing to assume the risk of using the innovation; they experiment and learn to adapt the innovation to local conditions. This category includes the first 2.5 percent of the adopters. The next 13.5 percent are the "early adopters." Farmers in this group play a key role in the diffusion process, because they are well respected by other farmers and exert a large degree of "opinion leadership." Next to adopt are the "early majority," which include 34 percent of the adopters. Farmers in this group deliberate for some time before adopting, waiting until sufficient experience has accumulated. Individuals in the "late majority" group (34 percent) are skeptics who are not convinced until most of their peers have adopted. The last group to adopt, the "laggards" (16

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[5] In addition, Gianessi and Puffer argue that pesticide reregistration has disrupted several successful IPM programs used in the production of fruits and vegetables. Because of the expense and time necessary to reregister pesticides, chemical manufacturers have dropped many of their low-volume products, including many selective pesticides necessary for IPM programs.

percent), are attached to tradition and suspicious of innovations and of "change agents." The laggards adopt only when they are certain that the innovation will not fail, because they cannot afford failure due to their "precarious economic condition."

A drawback of this classification scheme is that it is not exhaustive for innovations that never reach 100-percent adoption, because it excludes farmers who choose not to adopt. However, this problem is easily overcome by adding a longrun nonadopter category and renormalizing.

A New Consensus

The views described in this section form part of the adoption-diffusion perspective, which Ashby, Dunlap and Martin, and others criticized in the early 1980's. These critics accuse proponents of the adoption-diffusion perspective of having disciplinary blinders, neglecting crucial factors, such as the physical environment, in their analyses. More recently, a new consensus has emerged, integrating innovation-diffusion with physical, economic, and other factors (Nowak; Thomas, Ladewig, and McIntosh). This is the approach that we take to formulate our hypotheses and analyze the results.

Hypotheses About the Factors Influencing Adoption

This section examines farmer attributes and locational factors that are hypothesized to be influential in the decision to adopt IPM. These hypotheses are later tested in a logit regression framework.

Risk Perceptions

In agriculture, the notion that innovations are perceived to be more risky than traditional practices has received considerable support in the literature. Many researchers argue that the perception of increased risk inhibits adoption (Feder, Just, and Zilberman). When an innovation first appears, potential users are generally uncertain of its effectiveness and tend to view its use as experimental (Mansfield). Hiebert views adoption as a decision problem under uncertainty. He develops a model to examine the effect of learning under uncertainty on the decision to adopt fertilizer-responsive seed varieties. Feder and O'Mara further develop this idea using a Bayesian learning process to show that uncertainty declines with learning and experience, thus inducing more risk-averse farmers to adopt an innovation, provided it is profitable.

Risk is believed to be particularly critical in the adoption of a new technology for pest management because the effects of a subsequent crop loss are uncertain at the time a pest control strategy is used (Greene and others). Bultena and Hoiberg empirically support this view, finding that adopters are less risk-averse than nonadopters. Kovach and Tette find that users of apple IPM indicate "a greater willingness to accept some risk in order to use all the scientific knowledge available to protect their crop." On the other hand, they report that a large percentage of nonusers of IPM preferred to spray on an insurance or calendar basis.

In this study, the perception of risk is hypothesized to have a negative influence on IPM adoption. Innovators and early adopters of IPM are believed to be more inclined to take risks than are early- and late-majority farmers. Late adopters and laggards are likely to be even more risk averse.

To operationalize the concept of risk preferences using farmer attributes obtained from the survey, we consider three factors generally associated with a farmer's risk attitudes. The first, debt-to-assets ratio, measures financial risk. Robison and Barry show that the optimal debt is inversely related to risk aversion. It follows that optimal debt increases as risk aversion decreases. Given that early adopters are more inclined to take risks, we expect this variable to be positively correlated with

adoption. Next, we use crop insurance as a proxy for a grower's revealed reluctance to assume risk. When growers purchase crop insurance, they transfer a portion of the yield risk to the insurance agency. Thus, a farmer who purchases insurance reveals a risk-averse attitude that is also likely to be revealed in adoption.[6] Last, we use the total number of vegetable crops grown in a farm as a crude measure of output diversification, often associated with risk aversion (Freund).

Farm Structure

Another basic hypothesis is that the adoption of an innovation will tend to take place earlier on larger farms than on smaller farms. Just, Zilberman, and Rauser show that given the uncertainty, and the fixed transaction and information costs associated with innovations, there may be a critical lower limit on farm size, which prevents smaller farms from adopting. As these costs increase, the critical size also increases. It follows that innovations with large fixed transaction and/or information costs are less likely to be adopted by smaller farms. Nevertheless, Feder, Just, and Zilberman caution us that farm size may be a surrogate for other factors, such as wealth and access to credit, scarce inputs, or information.

Landownership is widely believed to encourage adoption. Several empirical studies support this hypothesis. The views expressed in the literature are not unanimous, however, and the subject has been widely debated (Feder, Just, and Zilberman). For example, Bultena and Hoiberg find no support for the hypothesis that land tenure had a significant influence on adoption of conservation tillage. In our view, the apparent inconsistencies in the empirical results are due to the nature of the innovation. Landownership is likely to influence adoption if the innovation requires investments tied to the land. Tenants are less likely to adopt these types of innovations because they perceive that the benefits of adoption will not necessarily accrue to them. Because IPM does not require land-tied investments, land tenure is not expected to affect IPM adoption.

Operator labor measures the amount of time that the operator dedicates to farm activities and is inversely related to off-farm labor. As McNamara and others argued, IPM requires a substantial amount of the operator's time. Off-farm employment may present a constraint to IPM participation, because it competes for onfarm managerial time. Thus, the availability of operator labor is hypothesized to have a positive influence on IPM adoption. Adoption of labor-intensive practices such as IPM is also expected to be positively associated with the availability of family labor.

Locational and Other Factors

Locational factors, such as soil fertility, rainfall, and temperature, influence profitability differences among farms. The physical environment of the farm may affect profitability directly through increased fertility, and indirectly through influence on pests. It is plausible that a farm located in a dry, infertile area is less likely to adopt IPM than a farm located in an adequately wet, fertile area. While weather (for example, monthly precipitation, temperature, and daylight hours), soil type, and other locational variables may affect the adoption decision, degrees of freedom and collinearity considerations often limit their use in a regression context. In this study, dummy variables for regions within a State are used as locational proxies to account for the potential effects of environmental factors on adoption.

Irrigation may also influence adoption. Irrigation generally increases yields and profitability and reduces production risk. However, irrigation may also increase pest risk, because it encourages

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[6]Moral hazard, in the sense that insurance purchasers would be more inclined to adopt IPM because they feel protected by the crop insurance, is unlikely to occur because a grower who purchases crop insurance can be protected up to only 75 percent of previous (average) yields.

certain pest populations (Harper and Zilberman). Therefore, the net effects of irrigation cannot be predicted a priori.

We use crop production variables to capture the effects of producing each major vegetable on IPM adoption. A positive (negative) and significant coefficient for a given vegetable crop indicates an increased (decreased) probability of IPM adoption if that crop is grown on a given farm. By comparison, livestock production is believed to limit IPM adoption, because livestock production is intensive in managerial and other labor.

Modeling Adoption Choices

A new technology will likely be adopted if its perceived utility is higher than the perceived utility of the old technology. Adoption of a new technology is essentially a choice between two alternatives, the traditional technology and the new one. As such, the choice models developed in consumer theory may be used to motivate the adoption decision. In this context, vegetable growers are assumed to make their decisions by choosing the alternative that maximizes their perceived utility. Because there are errors in optimization and perception, the utility function is assumed to be random (McFadden). Following Maddala, let U_{i1}^* measure the level of utility associated with the adoption of IPM by the ith grower, and let U_{i0}^* measure the level of utility associated with the current practice. The binary random variable Y_i takes the value of one if IPM is adopted and is expressed as

$$Y_i = \begin{cases} 1 & \text{if } U_{i1}^* = Max\,(U_{i1}^*, U_{i0}^*) \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

Utility is generally a function of a vector of choice characteristics (X_{ij}, $j = 1,0$); a vector of individual grower attributes and locational factors (Z_i); and a random disturbance (e_{ij}). Assuming a linear utility function, the utility of adopting IPM is $U_{i1} = Z_i'\,\beta_1 + X_{i1}'\,\gamma + e_{i1}$, and the utility of not adopting is $U_{i0} = Z_i'\,\beta_0 + X_{i0}'\,\gamma + e_{i0}$. The parameter vector γ is a constant, and the parameter vector β is alternative-specific. The stochastic component e_{ij} accounts for unobserved variations in preferences and errors in perception and optimization by the ith individual (Maddala). Following Fomby, Hill, and Johnson, the probability that the ith firm adopts IPM is given by: $P_{i1} = P[Y_i = 1] = P\,[U_{i1} > U_{i0}] = P[Z_i'\beta_1 + X_{i1}'\gamma + e_{i1} > Z_i'\beta_0 + X_{i0}'\gamma + e_{i0}] = P[(e_{i0} - e_{i1}) < Z_1'(\beta_1 - \beta_0\,) + (X_{i1} - X_{i0})'\gamma]$.

Individual attributes or characteristics must not have the same effect on utility, otherwise, the vector Z falls out of the model (Judge and others). Assuming that the stochastic components e_{i1} and e_{i0} are independently and identically distributed with a Weibull distribution, then their difference follows a logistic distribution (Maddala).

Due to limitations in the data, it is often assumed that choice probabilities depend only on observed individual-specific characteristics (Judge and others) In this case, the relative odds of adopting IPM are: $P_{i1}/P_{i0} = \exp\,(Z_i'\beta_1)/\exp\,(Z_i'\beta_0) = \exp\,[Z_i'(\beta_1 - \beta_0)]$; where, without loss of generality, it is customary to normalize setting $\beta_0 = 0$, or $\beta_1 - \beta_0 = \beta$. Taking the log of each side, the final equation is $\log\,(P_{i1}/P_{i0}) = Z_i'\beta$. For continuous variables, the change in the probability of adoption relative to the change of the kth individual attribute is

$$\frac{\partial P_i}{\partial Z_{ik}} = f(Z_i) = \frac{e^{-Z_i\beta}}{(1+e^{-Z_i\beta})^2} \cdot \beta_k \tag{2}$$

In the discrete case, the change in probability attributable to the kth variable or attribute is equal to the difference in probability $P_i (Z_{ik} = 1) - P_i (Z_{ik} = 0)$ (Putler and Zilberman).

Data and Estimation

The Agricultural Chemical Use Survey and its Economic Follow-On for vegetables were administered by the National Agricultural Statistics Service between October 1990 and February 1991 in Arizona, Florida, Texas, and Michigan.[7] This survey employed a two-frame probability sample: a list frame and an area frame. The list frame was based on all known commercial growers of fresh and/or processed vegetables, strawberries, or melons (hereafter called vegetables). These growers were required to have at least a tenth of an acre of production to be included on the list. In comparison, the area frame was taken from the 1990 June Agricultural Survey Tracts and was used only to provide additional information.

A stratified sampling technique was used to draw the sample. Each stratum is a mutually exclusive set of the commodities of interest. Farms are partitioned such that each farm is associated with only one stratum. With respect to IPM, each interviewed farmer was asked to report the use of scouting, parasites, biochemical or microbial agents, and cultural practices (rotation), which are usually considered to be IPM techniques. After excluding observations with missing values, 190 usable observations remained for Florida, 178 for Texas, and 160 for Michigan.

Commonly used econometric estimation methods are inappropriate in this study, because the survey data were obtained from a stratified sample. Unlike simple random sampling, the selection of an individual farm for the survey is not equally likely across all farms on the list. Some farms have a higher probability of selection than others. Differences in the probability of selection introduce bias in simple maximum likelihood (ML) estimates of the parameters and their variances. In this study, logit models are estimated using a weighted least squares version of the ML method, where the weights are equal to the inverse of the probability of selection. Separate logit regressions are run for each State.[8]

The dependent variable is a binary variable equal to 1 if one or more IPM techniques are adopted, 0 otherwise. The following factors or attributes are included in the model as regressors:

1. Size: Dummy variable equal to 1 if the farm is larger than 250 acres, 0 otherwise.

2. Operator labor: 1,000 hours per year.

3. Family labor: Unpaid family labor, 1,000 hours per year.

4. Debt ratio: Debt-to-total-assets ratio.

5. Number of vegetables: Discrete variable equal to the total number of vegetables grown.

6. Crop insurance: Dummy variable, 1 if crop insurance is purchased, 0 otherwise.

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[7]This survey forms part of the Pesticide Data Program (PDP), administered by USDA, which includes a series of surveys to collect data on pesticide use in the production of fruits, nuts, and vegetables. Arizona was excluded from our study due to the small number of usable observations.

[8]Pooling all the data together and using intercept shifters were not adequate. Large interstate differences in production structure, degree of adoption, weather, and soils affect both the intercept and the slopes of the logit regression.

7. Land tenure: Fraction of land owned by the operator.

8. Irrigation: Fraction of acres irrigated.

9. Livestock: Livestock revenues as a fraction of total revenues.

10. Locational dummies: Two regions are considered for both Florida and Texas. In Texas, the east, with an annual precipitation of more than 50 inches, includes the 51 eastern counties (EASTD = 1), and the west includes the remaining, drier counties (less than 8 inches of precipitation). In Florida, the south includes the 10 southern counties (SOUTHD = 1). Although precipitation differences between the south and north are minor, temperature differences have caused Florida's fresh winter vegetable production to be located primarily in the south. Dummies are not used in Michigan, because large regional differences are not observed.

11. Crop variables: Binary indicator variable for each of the main crops grown in each State: tomatoes, melons, and sweet corn for Florida; melons, onions, and cabbage for Texas; asparagus, cucumbers, and snap beans for Michigan. The binary variable equals 1 if the given crop is grown on that farm.

To help analyze the logit regression results, Rogers' classification is useful to characterize the types of farmers that comprise the adopter and nonadopter groups in each of the three States studied. However, we include the nonadopters category in addition to the five groups proposed by Rogers. That is, we divide the bell-shaped curve into six categories. An advantage of this modification is that the classification of adopter categories becomes mutually exclusive and exhaustive.

Results

Tables 1 and 2 present the results from the statistical analysis of the vegetable survey data. Table 1 provides the mean values of the variables used in the logit analysis for both adopters and non-adopters. For a binary indicator variable, the mean represents the fraction of growers of each group with that attribute. For example, the farm-size variable for Texas shows that 60.9 percent of the adopters operated farms larger than 250 acres, while only 34.2 percent of the nonadopters operated larger farms. In comparison, the continuous variables represent the actual means. For instance, the mean debt/asset ratio for Michigan adopters is 0.235 and 0.205 for nonadopters. Table 1 also shows the degree of IPM adoption for each State. In Florida, 30.5 percent of the farms have adopted IPM, compared with 38.8 percent in Texas, and 59.8 percent in Michigan. Because we also know that IPM adoption in 1970 was almost negligible for all three States, we use logistic functions to illustrate the IPM diffusion process (fig. 1).[9] Griliches notes that acceptance rates are due to differences between the profitabilities of the new and traditional technologies. This conclusion would imply that IPM techniques are more profitable for Michigan vegetable producers than for growers in the other two States. We do not have data to test this hypothesis, however.

Table 2 presents the logit regression results for IPM adoption for vegetable growers in Florida, Texas, and Michigan. The overall goodness of fit is excellent; especially compared with other studies of IPM adoption. The transformed log likelihood function, which is distributed chi-squared, is significant at the 1-percent level in each of the three States. Similarly, the McFadden R^2, which

[9]The longrun upper limit of adoption (K) assumed in this illustration is 90 percent. We emphasize that the curves illustrated in figure 1 are not meant to have any predictive capability.

Table 1—Means of variables used in logit analyses of vegetable farms in three States

Variable	Florida		Texas		Michigan	
	Adopters	Nonadopters	Adopters	Nonadopters	Adopters	Nonadopters
Size dummy	0.379	0.265	0.609	0.342	0.541	0.333
Operator labor, 1,000 hours/year	2.517	1.834	2.760	1.920	2.514	1.610
Unpaid family labor, 1,000 hours/year	.744	.427	.953	.575	1.944	.663
Debt/assets ratio	.325	.126	.200	.099	.235	.205
Irrigation, fraction of the acres irrigated	.566	.295	.367	.342	.214	.037
Livestock production, fraction of total revenues	.020	.104	.116	.273	.064	.118
Land tenure, fraction of acres owned by operator	.484	.587	.429	.572	.659	.777
Crop insurance dummy	.086	.091	.348	.149	.286	.197
Number of vegetables	2.140	2.010	3.120	2.640	2.230	1.270
Production:[1]						
Melon	.138	.424	.522	.456	NA	NA
Tomato	.293	.098	NA	NA	NA	NA
Sweet corn	.172	.242	NA	NA	NA	NA
Cabbage	NA	NA	.203	.061	NA	NA
Onions	NA	NA	.232	.237	NA	NA
Asparagus	NA	NA	NA	NA	.122	.379
Cucumber	NA	NA	NA	NA	.276	.152
Snap bean	NA	NA	NA	NA	.214	.047
SOUTHD/EASTD[2]	.172	.114	.203	.351	NA	NA
Number of farms	58	132	69	109	98	66
Percent of farms adopting	30.5	NA	38.8	NA	59.8	NA

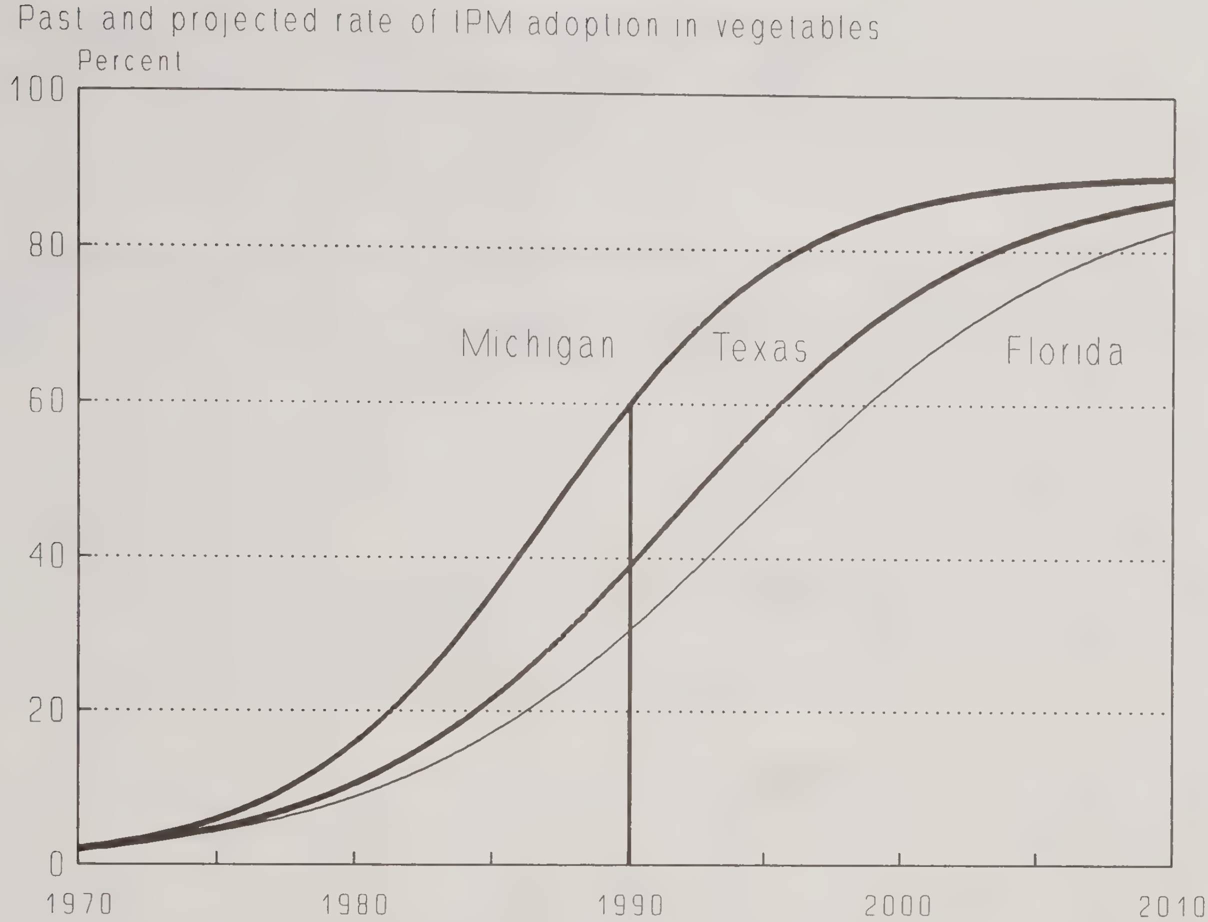
NA = Not applicable.
[1]Indicator variable defined in the text.
[2]SOUTHD for Florida and EASTD for Texas.

Table 2—Logit regression results of IPM adoption by vegetable growers in three States[1]

Dependent variable (IPM)	Florida		Texas		Michigan	
	Parameter estimates	Change in probability[2]	Parameter estimates	Change in probability[2]	Parameter estimates	Change in probability[2]
Intercept	-2.21 (.27)	NA	-2.78 (.26)	NA	-1.59 (.21)	NA
Size	.401* (.23)	.068	.723*** (.19)	.212	.100 (.18)	.009
Operator labor	.307*** (.097)	.050	.573*** (.09)	.097	.794*** (.10)	.371
Unpaid family labor	.434*** (.10)	.071	.103* (.06)	.018	.353*** (.07)	.098
Debt/assets ratio	1.04*** (.34)	.170	.988*** (.36)	.168	- .865*** (.30)	-.048
Irrigation	1.46*** (.28)	.239	1.28*** (.27)	.218	2.64*** (.56)	.063
Livestock production	-1.93** (.78)	- .316	-1.30*** (.32)	-.221	-2.57*** (.34)	-.056
Crop insurance	-.354 (.35)	-.052	(.116) (.20)	.020	- .082 (.20)	-.004
Number of vegetables	.047 (.08)	.008	.112*** (.04)	.019	.195*** (.07)	.082
Production:						
Melon	-1.94*** (.22)	-.287	.077 (.19)	.013	NA	NA
Tomato	1.17*** (.28)	.261	NA	NA	NA	NA
Sweet	-.111 (.28)	.019	NA	NA	NA	NA
Cabbage	NA	NA	1.39*** (.35)	.302	NA	NA
Onions	NA	NA	-1.65*** (.26)	-.202	NA	NA
Asparagus	NA	NA	NA	NA	-1.98*** (.20)	-.202
Cucumber	NA	NA	NA	NA	.605** (.24)	.023
Snap beans	NA	NA	NA	NA	2.28*** (.35)	.069
SOUTHD/EASTD[3]	-.780*** (.28)	- .015	.316 (.21)	.058	NA	NA
Number of observations	190	NA	178	NA	166	NA
-2 log likelihood function for covariates	359***	NA	313***	NA	945***	NA
McFadden R^2	.305	NA	.229	NA	.440	NA

NA = Not applicable. * Significant at the 10-percent level. ** Significant at the 5-percent level. *** Significant at the 1-percent level.
[1]Standard errors in parentheses. [2]Calculated at the means. [3]EASTD for Texas and SOUTHD for Florida.

Figure 1



cannot be compared with a traditional R^2, is within the upper range of most other studies. About 90 percent of the variables are statistically significant.

Among the risk factors, the debt-to-assets ratio in Florida and Texas is positive and significant at the 1-percent level, in agreement with our prior expectations. However, the debt-to-assets ratio in Michigan is significant and of the wrong sign. This may have been caused by the advanced degree of IPM adoption in Michigan compared with the other two States. As the degree of adoption increases, later adopters, who have different attributes than innovators and early adopters, are included in the adopters group. Adopters in Florida and Texas include all innovators, early adopters, and a fraction of the early majority (fig. 2). On the other hand, the adopters in Michigan include all innovators, early adopters, early majority, and a large fraction of late majority adopters (fig. 2). As a result, many of the differences in farmer attributes between adopters and nonadopters in Michigan become blurred, reducing the reliability of individual coefficients in the regression.

The crop insurance variable, which was used as a second proxy for risk aversion, does not appear to be related to adoption. The coefficient is negative as expected, but insignificant for Florida and Michigan. The coefficient is positive and insignificant in Texas. The third variable used to capture a grower's risk preference is the number of vegetable crops grown. The coefficient is positive as expected in all three States, although it is insignificant in Florida. The result for Florida appears to be due to the fact that the number of vegetables grown reflects other factors in addition to risk diversification; for example, on many farms, several crops may be grown sequentially on the same field during the same year. In any case, considering the overall effects of these three proxies of risk

Figure 2

Figure 2a
IPM adopter categories for Florida vegetables

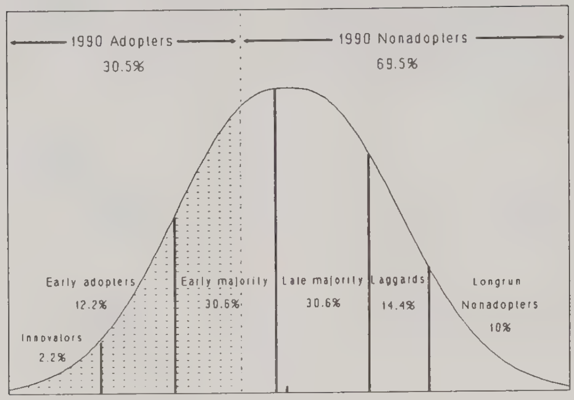


Figure 2b
IPM adopter categories for Michigan vegetables

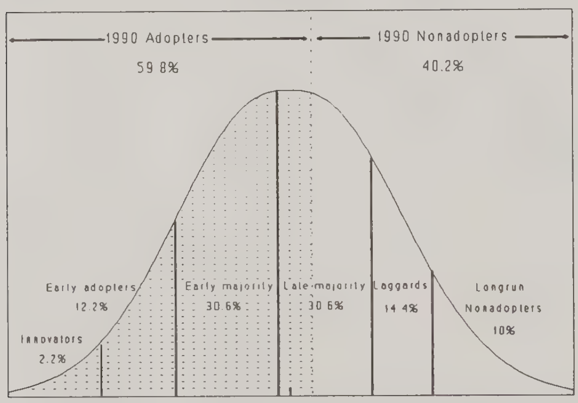
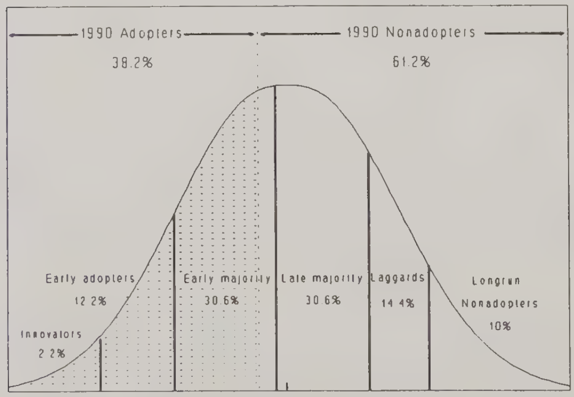


Figure 2c
IPM adopter categories for Texas vegetables



aversion, we reject the hypothesis that risk preferences have no influence on a grower's decision to adopt IPM.

For the variety of reasons mentioned earlier, large farms are more likely to adopt IPM than are smaller farms. In all three States, farm size is positively correlated with adoption. The coefficient is significant at the 10-percent level in Florida and the 1-percent level in Texas. The positive, yet insignificant, effect of farm size on adoption in Michigan is not surprising, given our observations on the relatively advanced degree of adoption in that State.

In all three States, operator labor, which also reflects off-farm activities by some operators, is significant and positive at the 1-percent level. This suggests that managerial time has significant influence in a grower's decision to adopt IPM. Unpaid family labor is also significant and positive in all three States; that is, availability of unpaid family labor increases the probability of adoption.

Irrigation is positive and significant at the 1-percent level in all three States. This finding suggests that the increased yield and profitability characteristics outweigh any increase in pest risk, which may be associated with irrigation in the IPM adoption decision. Only the regressions for Florida and Texas include location variables. In Texas, we find a positive but not significant (prob value = 13 percent) relationship between precipitation (prevalent in east Texas) and IPM adoption. In contrast, in Florida the relationship is negative and significant, suggesting that southern Florida growers were less likely to adopt IPM. The reason for this sign is unclear, although the increased incidence of pests in South Florida may partially account for this relationship.

The crop production variables are used to examine the effect of each major vegetable grown on IPM adoption. The production of five of nine vegetables increases the probability of IPM adoption. For example, the probability of IPM adoption is 26.1 percent higher for a grower producing tomatoes in Florida, compared with a Florida farmer not growing tomatoes. On the other hand, the probability of adoption is 28.7 percent lower for a Florida grower producing melons compared with a Florida grower not producing melons. With respect to the livestock production variable, we find a negative and significant effect of livestock production on IPM adoption in all three States. This finding supports our hypothesis that raising livestock limits the amount of time that the operator can devote to IPM.

The land tenure variable was dropped from the final model because, as hypothesized, the variable was statistically insignificant. While it is sometimes believed that adoption is positively correlated with landownership, as mentioned earlier, IPM does not require costly fixed capital, such as buildings, land improvements, or other investments tied to the land that a tenant would probably forgo. Rather, the IPM investment is in human capital, not tied to rented land.

Conclusions

A fundamental goal of agricultural economics research is to examine how farmers adopt new technologies. Given the distributional consequences of adoption, which became apparent in many countries after the Green Revolution, examining the influence of farm structure on technology adoption is particularly interesting. A unique feature of this study is the different degrees of adoption across these three States, ranging from 31 percent in Florida to 60 percent in Michigan. By incorporating into our analysis some perspectives of rural sociologists, especially the classification of adopters, we can improve our interpretation of the empirical results. In particular, the more advanced degree of IPM adoption in Michigan compared with the other two States explains the decreased reliability of several of the coefficients in the logit regression for Michigan.

Our results generally support the notion that early adopters are more inclined to risk-taking than are nonadopters. Farm size is a significant factor in Florida and Texas, confirming our expectation that large farms are more likely to adopt IPM than smaller farms. Furthermore, the positive, yet insignificant, effect of farm size on adoption in Michigan is expected, given the more advanced degree of adoption in that State. Operator and unpaid family labor are significant and positive in all three States, showing that both the quantity and quality of labor affect the adoption decision. Moreover, the significant and negative effect of the livestock production variable reinforces our hypothesis that managerial time is essential in the adoption of IPM.

IPM and irrigation are found to be complementary technologies, perhaps because the increased profitability that irrigation affords to farms also makes IPM profitable. Crop and locational variables are also influential in the IPM adoption decision. Farm ownership is not a factor in IPM adoption, however, because unlike many other technologies, IPM does not require investments tied to the land.

The data limit this study, particularly in relation to the amount of information on farmer attributes, such as education, age, and use of extension services. Also, the lack of information about the timing of various IPM practices in relationship to different pest populations prevents a sequential analysis of the decision process.

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